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# CRIME UNDERREPORTING: THEORY AND IMPLICATIONS FOR THE STATISTICAL ANALYSIS OF CRIME

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# CRIME UNDERREPORTING: THEORY AND IMPLICATIONS FOR THE STATISTICAL ANALYSIS OF CRIME

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Abstract: The paper specifies a model of the crime reporting decision by victims and tests the model using city level data from victimization surveys. The results of the estimation are used to explore and evaluate the biases underreporting can induce in statistical models based upon reported crime rates.

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# Crime Underreporting: Theory and Implications for the Statistical Analysis of Crime

## Introduction

During the past ten years we have witnessed a great increase in both public concern regarding crime levels and in professional concern directed towards the analysis of crime, its causes, its effects and the appropriate policies for its social control. This heightened concern has also resulted in a greater interest in the measurement of crime; crime--unlike many other phenomena--is 'observed' by most people only through official statistics. Since most people are not direct victims of criminal acts, 'crime waves'--unlike severe winters or high rates of inflation--are communicated to the general public only by statistics. Further, these statistics are based for the most part, on voluntary reports of the victims of crimes and then 'validated' by police departments before they become public knowledge.

Because of this process, particularly the reliance upon voluntary reporting by victims, criminologists have long believed that there exists a large amount of unreported crime, the so-called 'Dark Figure' of crime. However, it was not until the introduction of victimization surveys of the general population in the early 1970's that the magnitude of the Dark Figure was documented. These surveys have found that overall only a third of all victimizations are reported to the police [15; Table 89]. However, the findings of the victimization surveys had implications not only for documenting the magnitude of the level of crime but for the analysis of crime as well.

The last ten years has also seen a great increase in the scholarly interest in crime, an interest which has also become much more interdisciplinary than in the past. In particular, economists and political scientists have joined criminologists and sociologists in the analysis of crime. Economists, in particular, have also brought alternative theoretical and methodological approaches to the area. The traditional focus of analysis on offenders--their characteristics and motives--has been supplemented by a more macro approach, the analysis of crime rates in populations using causal models based on economic theory. This new empirical emphasis has given an additional significance to the phenomena of crime underreporting in addition to the accurate measurement of crime rates for descriptive purposes.

All statistical analyses of crime rates based upon the 'economic model' of crime have as a central theoretical assumption the deterrence hypothesis. This is the assumption that criminals--potential and actual--are sufficiently rational that the threat of punishment will influence their decision to engage in criminal acts. Consequently, this theory predicts that there should be an inverse relationship between the threat of punishment, measured by certainty and/or severity, and the rate of crime, other factors held constant. The question of whether a significant number of criminal acts is the result of rational choice, of course, has immediate policy implications. If the deterrence hypothesis is correct, then increasing the threat of punishment should, in theory, offer an effective means of controlling the level of crime.

The majority of the statistical analyses of crime rates which introduce the deterrence hypothesis have produced results consistent with the hypothesis, i.e., they find an inverse relationship between the crime rate and the level of punishment, measured by certainty and/or severity. Nevertheless, these findings have been given conflicting interpretations. The researchers themselves generally interpret the findings as empirical confirmation of the deterrence hypothesis. Others who have reviewed the same findings are more skeptical in accepting the deterrence hypothesis [5], [10]. The Panel on Research on Deterrence and Incapacitive Effects of the National Academy of Sciences has recently subjected a large number of these statistical analyses to a searching methodological critique. The Panel concluded:

> In summary, therefore we cannot yet assert that the evidence warrants an affirmative conclusion regarding deterrence. We believe that scientific caution must be exercised in interpreting the limited validity of the available evidence and the number of competing explanations for the results. [2; 7]

One of the competing explanations, accorded much weight by the Panel, was based upon the phenomena of unreported crime. It has been shown that if the rate of unreported crime varies randomly across populations comprising the sample and if the deterrence variable is a ratio with the crime rate in the denominator (e.g., the percent of crimes cleared by arrest, the arrest rate per crime, the average prison sentence per crime, etc.) then the random variation in the underreporting rate can induce a negative correlation between the crime rate and the deterrence variable [6], [14]. Thus, there exists the possibility that the findings of a negative relationship in the statistical studies using such deterrence variables may be in part or entirely a statistical artifact.

However this impact of underreporting is dependent upon two conditions: that there is random variation in the underreporting ratio between populations in the sample and that the measure of deterrence includes the crime rate in the denominator. In addition to this potential for confounding the statistical results there exists two other general impacts of underreporting on statistical models of crime rates utilizing multiple regression techniques. The first, and most general, is that underreporting introduces measurement error in the dependent variable. If this error was non-stochastic it would affect only the constant term but not the estimated coefficients; however, if it was purely stochastic (i.e., purely random) then the additional variability imparted by the variation in the measurement error would increase the standard errors of the coefficients and thus increase the possibility that a true relationship would be undetected. Consequently, in general, random underreporting error may either artifactually produce <u>support</u> or <u>rejection</u> of the deterrence hypothesis.

A second source of potential difficulties caused by underreporting is based on the assumption that the underreporting error is stochastic but with a systematic component, i.e., it is not purely random. If the rate of underreporting is dependent upon either the rate of crime in the population or any of the independent variables in the crime rate equation, then one or more of the coefficients in the regression equation will be biased.

The primary purpose of this paper is to explore the possibility that crime underreporting may be explained by systematic factors, i.e., that the variation in observed crime reporting ratios between cities is not purely random. We approach the question by first specifying a theory of crime underreporting that may be applied to populations--cities. When this theory is confronted with data we find that there does exist a systematic component to the variation in underreporting. We then explore the implications of this systematic component as a source of bias to coefficients in two typical regression models used to analyze crime rates.

## A Theory of Crime Underreporting

One of the major objectives of the National Crime Survey was to obtain information from victims regarding their decision to report or not to report their victimization to the police. In the 1975 survey, the major reasons given for failure to report were:

| Reason Given | All Personal Crimes | All Househould Crimes |
|---|---|---|
| Nothing could be done; lack of proof | 29.9% | 36.2% |
| Not important enough | 25.4 | 29.1 |
| Police would not want to be bothered | 6.1 | 9.0 |
| Private or personal matter | 5.4 | 5.2 |

Source: [15; Table 98].

Because of the very general nature of these answers, the survey data have been analyzed to determine which major objective characteristics of the event and the victim are correlated with the reporting decision. The motivation of these studies has been to advance our knowledge of 'victimology'--characteristics of victims, the impact of crime on them, and their interrelationship with the criminal justice system. The motivation of this paper, however, is primarily to explore the implications of non-reporting for the analysis of crime rates. In victimology studies, the unit of observation has been the individual rather than populations; nevertheless, the results of these studies are a useful starting point for our analysis.

The major finding of this analysis has been that the degree of nonreporting differs significantly among crime types; that the characteristic of the victimization event, within crime type, is a better predictor of nonreporting than the characteristics of the victim, e.g., age, race, income, educational level and marital status [9]. Age was the only victim characteristic found to be important. The important characteristics of the victimization event for predicting reporting are: seriousness of the victimization (monetary loss or injury), or the use of a weapon. In addition to these objective factors some studies have explored the role of attitudes of the victims toward the criminal justice system as a factor in nonreporting, in particular their attitudes toward the police [8], [12]. One study confirmed the major importance of seriousness as an explanatory variable, but found that for the less serious crimes attitudinal variables are also important. The variables include: the victims involvement in the community, the belief that the police will be able to catch the offender, and the victim's trust in the police.

Our theory of crime reporting decision is based upon the weighting of the personal costs and benefits to the victim of reporting. The benefits may be grouped into three classes:

i) recovery of stolen property for property crimes

ii) increased future safety from apprehension of the offender. This would also include a concern for other potential victims--good citizenship--as well as for oneself.

iii) retribution, a desire to have the offender apprehended and punished as a matter of just deserts.

The personal costs would include the following:

i) the cost in lost time and perhaps lost income from reporting and possible subsequent involvement as a witness.

ii) psychological unpleasantness of involvement with the police, i.e., the possibility of not being believed and embarrassment from admission of culpability or carelessness.

iii) personal cost that reporting might have in subsequent relationships with the offender, e.g., fear of reprisal or an emotional tie to the offender.

This general framework, limited by data availability, is implemented by the following variables or proxy variables. The economic benefits are measured by the average property loss for each type of crime; the higher the average loss the greater potential return from reporting the matter to the police. Also, police efficiency in recovering the property should also be a consideration. The most direct measure of this would be the percent of stolen property recovered for each type of crime. However, this is not available for all cities, and then it is available only for all property crimes, not specific crimes. Another source of benefits is increased future safety if the offender is apprehended. This concern for future safety would increase the probability of reporting the higher the perceived risk of victimization and the more efficient the police. The risk of victimization is measured by the reported crime rate and police efficiency is measured by the arrest clearance rate as well as the subjective evaluation of police performance.

The personal cost of reporting crime cannot be readily captured with any precision, given available data at the city level. But two proxy variables are used, the first is the number of police per capita. The greater the number of police, the less time required in searching and/or waiting for a police officer to appear. The second is the subjective evaluation of the quality of the local police. The more positive this evaluation, the less threatening would be the contact with the police.

## Data and Estimation Results

The basic city sample was defined by the 26 cities in which victimization surveys have been conducted from 1971 through 1975. Of these 26 cities, 13 have been surveyed twice and 13 surveyed only once [17], [18], [19]. Thus a pooled sample could produce at most 39 observations. However, missing data from the Uniform Crime Reports reduced the available sample size to 30. The National Crime Survey data provided both the crime reporting ratios for each city by crime type and a measure of the city population's opinion about local police performance [20]. This portion of the survey asked each respondent to evaluate local police performance as 'good', 'average', or 'poor'. We have used the percent responding 'good' as our measure of the subjective evaluation by the city population of their police.

Table 1 presents the results of regressions using as the dependent variable the crime reporting ratio for all property crimes and four specific property crimes. Turning first to the reporting ratio for all property crimes, reporting behavior was significantly related to only two of the six variables. These were the property crime rate and the number of police per capita; both coefficients have a positive sign as predicted by the theory. These results are consistent with the hypotheses that people tend to report crimes to a greater extent the more serious the crime problem is in their city--at least as measured by property crimes known to the police--and that reporting is higher when the personal inconvenience is low; inconvenience is measured by the number of police per capita.

Neither of the objective performance measures of the police--clearance rate or stolen property recovery rate--was associated with reporting ratios, nor was the public evaluation of police performance associated with the reporting ratio. Surprisingly, the average loss per property crime was not a significant determinant of crime reporting. Analysis of individual victimization data found a strong association between loss and reporting [9]. The failure of this association to be confirmed with the present data may be attributed to the lower variation in average losses between cities as compared with variation in losses of individuals within a given city.

Among the four specific property crimes, auto theft reporting was not associated with any of the variables. Auto theft differs, in important ways from the other types of theft. First, there is a relatively high reporting ratio for this type of crime--73% in the sample

## Table 1 - Property Crimes

| Independent Variables: | Dependent Variable - Crime Reporting Ratio for: All Crimes of Theft | Auto Theft | Personal Larceny With Contact | Personal Larceny Without Contact | Burglar |
|---|---|---|---|---|---|
| Property Recovery Ratio | 3.08 (0.52) | 2.52 (0.38) | 6.90 (0.80) | -4.42 (-0.92) | -8.85 (-1.97) |
| Average Loss, Specific Crime | -- | -.003 (-1.61) | -0.03 (-1.32) | -0.03 (-1.69) | -0.000 (-0.03) |
| Average Loss, All Property Crimes | 0.00004 (1.07) | -- | -- | -- | -- |
| Clearance Rate, Specific Crime | -- | 16.39 (1.42) | -.0028 (-1.96)* | -12.05 (-1.50) | 8.61 (1.23) |
| Clearance Rate, All Property Crimes | -6.40 (-0.54) | -- | -- | -- | -- |
| Property Crimes per Capita | 77.71 (3.19)** | 45.29 (1.59) | 36.92 (1.05) | 62.65 (3.21)** | 64.68 (3.31) |
| Police Officers per Capita | 1905. (4.20)** | -152.3 (-0.27) | 1413. (1.95)* | 1416. (3.52)** | 1099. (2.8)* |
| Percent of Population Evaluating Police Performance as 'Good' | 0.130 (1.67) | -0.167 (-1.64) | 0.22 (1.84)* | 0.079 (1.16) | -0.01 (-0.14 |
| Adjusted $R^2$ | .40 | .07 | .27 | .48 | .41 |

**Significant at 5% level     *Significant at 10% level

cities used. Second, the variation in the reporting ratio between the cities for this crime was relatively low. No doubt the widespread use of theft insurance for automobiles effects reporting auto thefts.

The reporting of personal larceny with contact equation produced two anomalies; first the clearance ratio was significant but with the opposite sign predicted by the theory. There is no obvious theoretical reason why higher clearance rates should be associated with lower reporting ratios. This equation was also the only instance where the evaluation of police performance by population survey was significant and positively associated with reporting. The personal larceny without contact reporting ratio was significantly associated with only the level of property crimes and police officers per capita, but these associations were strong enough to give this equation the best fit of any of the five.

The burglary reporting equation was similar in results to the personal larceny without contact equation except for a significantly negative coefficient for the property recovery ratio. This is again the opposite of what the theory would predict; however, it should be remembered that the property recovery ratio used is for all property crimes not just burglary; consequently, given the crudeness of the proxy little importance should be attached to this perverse result.

Among the eight independent variables only the property crimes per capita and police officers per capita showed any consistent and significant association with the crime reporting decision among the cities in the sample.

The results for the reporting ratios of crimes of violence are given in Table 2. The reporting of all crimes of violence collectively was significantly associated with only two variables, the overall level of violent crime and the police officers per capita. The signs of both coefficients were positive as predicted. While the theory views each of these variables as measuring independent influences on reporting behavior, given the nature of the criminal justice system, some positive correlation would be expected between them. One would expect citizens concern to be highest and political response to be greatest if their city is experiencing high levels of violent crime. One positive response produced by this concern would naturally be to obtain more police protection. We find such a direct association to be present in the sample, but not overly strong; the simple correlation is +.47.

The reporting ratio equation for rape is just significant; only police officers per capita show any association and then only marginally so. This result is not particularly surprising, given the inability to find any proxies for the personal costs of reporting. The other specific crime reporting ratios, robbery and aggravated assault only show a significant positive association with the level of violent crime as hypothesized.

Since the theory offers no guidance as to the functional form of the relations, the equations were estimated in logarithmic form; these results are reported in Tables 3 and 4. The change in functional form produced very few changes in the pattern of signs and statistical significance of the coefficients. The coefficients now, however, represent

Table 2 - Violent Crimes

Dependent Variable - Crime Reporting Ratio for:

| Independent Variables: | All Violent Crimes | Rape | Robbery | Aggravated Assault |
|---|---|---|---|---|
| Property Recovery Ratio | | | 10.07 (1.38) | |
| Average Loss, Specific Crime | | | .008 (0.71) | |
| Property Crimes per Capita | | | | |
| Clearance Rate, Specific Crime | -- | 9.24 (0.64) | 5.70 (0.70) | 3.72 (0.50) |
| Violent Crimes, per Capita | 525. (3.82)** | 216. (0.59) | 539. (2.55)** | 375. (2.24)** |
| Total Crimes, per Capita | -17.4 (-0.90) | -- | -- | -- |
| Police Officers, per Capita | 1007. (2.44)** | 2139. (1.74)* | 987. (1.53) | 472. (0.86) |
| Percent of Population Evaluating Police | .028 (0.38) | -.319 (-0.14) | .086 (0.68) | -.006 (-0.06) |
| Adjusted $R^2$ | .67 | .14 | .34 | .28 |

**Significant at 5% level    *Significant at 10% level

Table 3 - Property Crimes - Variables in Log Form

| Independent Variables: | Dependent Variable - Crime Reporting Ratio for: All Crimes of Theft | Auto Theft | Personal Larceny With Contact | Personal Larceny Without Contact | Burglary |
|---|---|---|---|---|---|
| Property Recovery Ratio | -.0531 (-0.73) | .0137 (0.42) | .0589 (0.71) | -.0877 (-1.45) | -.0623 (-2.22) |
| Average Loss, Specific Crime | -- | -.0289 (-1.05) | -.1098 (-1.32) | -.1326 (2.16)** | -.0155 (-0.52) |
| Average Loss, All Property Crimes | -.0220 (-0.62) | -- | -- | -- | -- |
| Clearance Rate, Specific Crime | -- | .0371 (1.46) | -.1810 (2.29)** | -.0970 (-1.67) | .0131 (0.50) |
| Clearance Rate, All Property Crimes | -.0593 (-0.72) | -- | -- | -- | -- |
| Property Crimes per Capita | .1975 (2.51)** | .0473 (1.28) | .0721 (.082) | .2078 (3.25)** | .0994 (3.16)* |
| Police Officers per Capita | .3302 (4.23)** | -.0032 (-0.08) | .1764 (2.04)** | .2379 (3.75)** | .1152 (3.65)* |
| Percent of Population Evaluating Police Performance as 'Good' | .2006 (1.71)* | -.0886 (-1.46) | .2478 (1.88)* | .1186 (1.22) | .0418 (0.83) |
| Adjusted $R^2$ | .36 | .03 | .27 | .50 | .45 |

**Significant at 5% level　　　*Significant at 10% level

Table 4 - Violent Crimes - Variables in Log Form

Dependent Variable - Crime Reporting Ratio for:

| Independent Variables: | All Violent Crimes | Rape | Robbery | Aggravated Assault |
|---|---|---|---|---|
| Property Recovery Ratio | -- | -- | .0763<br>(1.60) | -- |
| Average Loss, Specific Crime | -- | -- | .0467<br>(0.94) | -- |
| Clearance Rate, Specific Crime | -- | .1236<br>(0.76) | .0455<br>(0.81) | .0592<br>(0.62) |
| Violent Crimes, per Capita | .1099<br>(2.75)** | -.0064<br>(-0.06) | .1324<br>(2.47)** | .0596<br>(1.36) |
| Total Crimes, per Capita | -.0090<br>(-.21) | -- | -- | -- |
| Police Officers, per Capita | .1246<br>(2.82)** | .2257<br>(2.00)** | .0910<br>(1.70)* | .0716<br>(1.38) |
| Percent of Population Evaluating Police | .0016<br>(0.02) | -.0655<br>(-0.35) | .0801<br>(0.92) | -.0422<br>(-0.49) |
| Adjusted $R^2$ | .63 | .11 | .34 | .23 |

**Significant at 5% level  *Significant at 10% level

elasticities--the proportional response of the reporting ratio to proportional changes in the independent variable. The values of the elasticities which were significant were generally small, ranging from 0.1 to 0.2. The highest, 0.33, was the response of the reporting ratio for all property crimes to changes in police per capita. While this seems high, a more precise framework for evaluating the magnitudes of the coefficients will be provided in the following section.

In summary, only two of the eight independent variables show any consistent significant association with the crime reporting ratios; these are the crime rate itself and the number of police per capita. The crime rate was always positive and significant in both of the aggregated crime types and significant in four of the seven specific crime equations. Police officers per capita was also positive and significant in both aggregate crime equations and in four of the specific crime equations. It is not particularly surprising that none of the proxies for police performance performed well, as these would require knowledge of police activities which the typical citizen would not possess. It is surprising that the general subjective evaluation of police performance revealed by the population surveys showed almost no significant relationship with reporting behavior; however this result is consistent with one analysis of individual reporting decisions [8]. We now explore the implications of these findings for the statistical analysis of crime rates.

Crime Underreporting and the Statistical Analyses of Crime:

The effect of crime underreporting on the statistical analysis of crime rates depends, of course, upon the statistical model that is employed to explain variations in crime rates across the sample units.

In the literature one finds a range of sophistication in statistical methods and models ranging from simple zero order correlation to multi-equation simultaneous equation models. However, given the complexity of crime causation, a multivariate model as a minimum, would be required. We will consider the effect of crime underreporting on both single equation and simultaneous equation models.

A simple single equation model of the true crime rate, c*, with all variables expressed, in logarithms, is:

(1) $c^* = \alpha_0 + \alpha_1 o + \alpha_2 p + \alpha_3 x + e$

where: o = police officers per capita

p = average punishment awarded upon conviction

x = other socio-economic or demographic variable, e.g., level of unemployment

e = error term

$\alpha_i$ = parameters to be estimated

If reported crime, c, is a fraction, k, of true crime, then in logarithms:

(2) $c = c^* + k(\cdot) + u$

where $K(\cdot)$ is a function determining non-random reporting behavior and u is an error term.

Crime reporting behavior, based upon the earlier analysis, is approximated in logarithms by:

(3) $k = k_0 + \eta o + \lambda c$

Substituting (3) into (2) we obtain the reported crime rate as influenced by reporting behavior:

$$(4)\quad c^* = (1-\lambda)c - k_0 - \eta o - u$$

Substituting (4) into (1) and solving for reported crime, c, we obtain the equation which is actually estimated:

$$(5)\quad c = \frac{1}{1-\lambda}\,[k_0 + \alpha_0 + (\eta + \alpha_1)o + \alpha_2 P + \alpha_3 x + (e + u)]$$

The estimated effect of police officers per capita on reported crime will not be the $\alpha_1$ hypothesized in equation (1) but rather a coefficient reflecting systematic variation in crime reporting as well as the direct effect, $\alpha_1$; this estimated coefficient, $\hat{\alpha}$, is:

$$(6)\quad \hat{\alpha}_1 \equiv \frac{(\eta+\alpha_1)}{(1-\lambda)}$$

To determine whether $\hat{\alpha}_1$ will be larger or smaller than $\alpha_1$ we must consider the probable signs of all the terms in the expression. Theory would predict that $\alpha_1$ is negative, on the assumption that more police will increase the risk of arrest and conviction. Both the theory of crime reporting and estimates given above suggest that $\eta$ and $\lambda$ are positive. The effect of $\eta$ is to bias $\hat{\alpha}_1$ downwards, i.e., the dependence of the reporting ratio on police officers per capita can lead to a rejection of a true hypothesis that law enforcement activity, as measured by police per capita, has any effect on reported crime. The logic is quite straightforward, more police will simultaneously reduce crime and increase the proportion of real crime reported; the net impact on reported crime may be nil or even positive.

In addition, $\lambda$ can also affect the sign as well as the magnitude of $\hat{\alpha}_1$. If $\lambda$ is greater than unity, it will reverse the sign of $\hat{\alpha}_1$. However, the evidence on the magnitude of $\lambda$ reported in tables 3 and 4 indicates its value is in the range of .1 to .2; consequently, it seems unlikely that $\lambda$ will reverse the sign of $\hat{\alpha}_1$. If $\lambda$ is assumed to be less than unity, the bias will be to increase the absolute value of $\hat{\alpha}_1$. That is, the effect of $\lambda$ will be to spuriously over-estimate the impact on the crime rate not only of law enforcement activity but of all the variables. For example, consider the unemployment rate as a determinant of the crime rate. A rise in unemployment will increase the true crime rate and, with a constant reporting ratio, the reported crime as well. However, if the increased reported crime rate now increases the reporting ratio, the observed impact of unemployment on reported crime will be further and spuriously increased.

Since underreporting behavior operates both to increase and to decrease $\hat{\alpha}_1$, we cannot determine, with theory alone, even the direction of the bias. We can gain some further insight, however, by utilizing information obtained for the values of $\eta$ and $\lambda$ from the earlier analysis and by making some assumptions as to the true value of $\alpha_1$. Theory suggests that $\alpha_1$ should be negative, thus one bound on possible true value of $\alpha_1$ is zero, i.e., police officers per capita has no true effect on the level of crime. For the other bound we will use -1.0 as the elasticity of the crime rate to variations in police officers per capita. The only support we can offer for this as a bound is the general impression from the literature that crime is relatively insensitive to the level of law enforcement activity. An elasticity of 1.0

would thus seem reasonable as an outside bound. For values of $\eta$ and $\lambda$ we use the estimates for property crime and violent crime given in tables 3 and 4. Using these values and equation (6) we have computed Table 5.

Table 5

| True value of $\alpha_1$ | Biased Estimates of $\alpha_1$ Using Equation (6): Property Crime Rate: $\eta = .33$; $\lambda = .20$ | Violent Crime Rate: $\eta = .12$; $\lambda = .11$ |
|---|---|---|
| 0 | +.41 | +.13 |
| -.2 | +.24 | -.09 |
| -.5 | 0 | -.43 |
| -1.0 | -.42 | -.99 |

Table 5 shows that over the range of values assumed, the effect of underreporting behavior is to bias the absolute value of $\hat{\alpha}_1$ upwards. The smaller the true value of $\alpha_1$, the greater the relative bias. For property crime, the true elasticity would have to be .5 in absolute value or greater before we would even expect the estimate to have the correct negative sign.

We conclude that for the single equation model we have used, the systematic component to variations in reporting behavior will bias towards zero the effect of police per capita on crime rates, but will bias upwards in absolute value the effects of all other variables.

A simultaneous model is appropriate if the level of crime affects the level of sanctions as well as the level of sanctions affects the level of crime. This mutual causation follows from an assumption that one or more units of the criminal justice system has a capacity constraint. For example, it is argued that increased crime produces an increased workload for the police and as a result, with constant resources, reduces their ability to solve crimes--the clearance rate declines. A similar argument may be applied to the courts or to prisons. An increased case load for the prosecutors or judges may lead to greater use of negotiated pleas, thus reducing the charge and the average punishment. Similarly, parole board decisions may be influenced by the prison population relative to prison capacity. As a rise in crime pushes prisons to capacity parole boards may more readily grant parole to avoid overcrowding and thus again reduce the average sentence served.

Some degree of simultaneity between crime and sanctions has become a standard assumption in econometric models. A good example of such a model is that of Carr-Hill and Stern; they also introduce the possibility of crime underreporting in their model [3]. An abridged version of their model with all variables in logarithms is:

$$(7)\quad c^* = \alpha_1 p^* + \alpha_2 o + \alpha_3 x + \alpha_0 + e_1$$

$$(8)\quad p = \beta_1 c + \beta_2 o + \beta_3 y + \beta_0 + e_2$$

$$(9)\quad o = \gamma_1 c + \gamma_2 p + \gamma_3 z + \gamma_0 + e_3$$

$$(10)\quad p^* + c^* \equiv p + c$$

$$(11)\quad c = c^* + k(\cdot) + u$$

where $c$ = reported crime rate

$c^*$ = true crime rate

$p$ = probability of punishment based upon the reported crime rate, e.g., the police clearance rate

$p^*$ = probability of punishment based upon the true crime rate

$o$ = police officers per capita

$x,y,z$ = other exogenous variables

$k$ = crime reporting ratio

$k(\cdot)$ = function determining reporting behavior

$e_i$, $u$ = error terms

$\alpha_1,\beta_1,\gamma_1$ = parameters to be estimated

Equation (7) gives the true level of crime as a function of the true risk of punishment, police officers per capita and other exogenous variables, e.g., the unemployment rate or age distribution of the population. This specification assumes that police officers per capita have two effects on the true level of crime; an indirect effect which operates through the true probability of punishment and second, a direct effect. That is, some criminals may measure risk through the actual level of punishment while others may infer risk by direct observation of the number of police present.

Most econometric models implicitly assume that only the direct effect is operative. Such an assumption facilitates identification and is consistent with the theory which assumes that potential criminals are 'rational', i.e., they know the true risk. However, there is no evidence as to how potential offenders actually determine risk [21].

Equation (8) is a punishment production function where the inputs are the number of police and the number of crimes plus other factors. Equation (9) describes the major determinants of the number of police per capita; it assumes that the political process which establishes police department budgets is sensitive to the level of reported crime and the level of probability of punishment as well as other variables. Equation (10) is an identity which simply states that the number of crimes cleared equals the number of crimes cleared; it permits the replacement of p* with observed variables. Equation (11) assumes that reported crime is some fraction, k, of the true level of crime. Equations (10) and (11) are needed to replace the true, but unobservable, values of crime and punishment in equation (7) with observed or reported values.

Substituting (10) and (11) into (7) to eliminate c* and p*, we obtain an equation for reported crime:

$$(12)\quad c = \alpha_1 p + k(\cdot)(1+\alpha_1) + u(1+\alpha_1) + \alpha_2 o + \alpha_3 x + \alpha_0 + e_1$$

Based upon the findings of our earlier analysis we assume that the crime reporting ratio is determined as follows:

$$(13)\quad k(\cdot) = k_o + \lambda c + \eta o$$

where $k_o$ is a constant, $\lambda$ and $\eta$ are parameters.

Substituting (13) into (14) we obtain:

$$(14)\quad c = \frac{1}{1-\lambda(1+\alpha_1)}\{\alpha_1 p + [(1+\alpha_1)\eta + \alpha_2]o + (1+\alpha_1)k_o + \alpha_3 x + \alpha_0 + (1+\alpha_1)u + e_1\}$$

The term in front of the braces is introduced by the dependence of the reporting ratio on the level of reported crime; it introduces a bias to all of the coefficients in the equation. Assuming that $\alpha_1$ is negative and less than one in absolute value and that $\lambda$ is positive but less than one, then the bias from this source will be to increase all of the coefficients in absolute value. If $\alpha_1$ were exactly minus one in value, then there would be no bias; if it were larger than one in absolute value, then the bias would reduce all of the coefficients in absolute value.

There is an additional source of bias to the coefficient for police per capita, $\alpha_2$; this bias is introduced by the dependence of the reporting ratio on police per capita. The estimated coefficient, $\hat{\alpha}_2$, taking account of both sources of bias, is:

$$(15) \quad \hat{\alpha}_2 = \frac{(1+\alpha_1)\eta + \alpha_2}{1 - \lambda(1+\alpha_1)}$$

The expression on the right hand side of (16) cannot be evaluated as to the direction of the bias without some assumptions for the values of the parameters. To explore the qualitative nature of the bias, we assume that $\alpha_1$ and $\alpha_2$ are negative and less than unity and use values for $\lambda$ and $\eta$ estimated from reporting behavior for property crimes and violent crimes and reported in Tables 3 and 4. With these assumed values we can evaluate equation (15) for various combinations of values; these results are given in Table 6.

Table 6

Biased Estimates of $\alpha_2$ Using Equation (15)

| Assumed value of $\alpha_1$: | Property Crime Reporting: ($\eta = .3$; $\lambda = .2$) Assumed true value of $\alpha_2$: 0 | -.2 | -.5 | -1.0 | Violent Crime Reporting: ($\eta = .1$; $\lambda = .1$) Assumed true value of $\alpha_2$: 0 | -.2 | -.5 | -1.0 |
|---|---|---|---|---|---|---|---|---|
| 0 | +.38 | +.13 | -.25 | -.88 | +.11 | -.11 | -.44 | -1.0 |
| -.2 | +.28 | +.05 | -.31 | -.90 | +.09 | -.13 | -.46 | -1.0 |
| -.5 | +.17 | -.06 | -.39 | -.94 | +.05 | -.16 | -.47 | -1.0 |
| -1.0 | 0 | -.2 | -.5 | -1.0 | 0 | -.2 | -.5 | -1.0 |

The magnitude of the bias of the police officers per capita coefficient is relatively minor for crimes of violence over the range of values used in Table 6. Only for quite small true values of $\alpha_2$ is the bias at all large in percentage terms. For property crimes, however, the magnitude of the bias is much greater, over 50% in many cases. This difference is due, of course, to the stronger dependence of the reporting ratio on the crime level and number of police per capita. In every instance the bias is towards increasing the estimated value relative to the true value; since the true value should be negative if the presence of police deter crime, the bias will tend to reduce the measured direct impact of police on crime.

In summary, we have found that the bias from underreporting of crime has the same general impact in the simultaneous model as in the single equation model. The dependence of reporting behavior on the reported level of crime will bias all coefficients upwards in absolute value, i.e., the bias will tend to lead to a spurious rejection of the null hypothesis. The impact of the dependence of reporting behavior on police per capita will tend to bias the coefficient of police per capita towards zero, i.e., to lead to a spurious rejection of the null hypothesis. This source of bias is sufficiently strong that it dominates the total bias from both sources for plausible ranges of the relevant parameters. Further, the smaller the true effect of police per capita on crime, the larger the total bias in percentage terms. That is, a small true value will not only be difficult to find because of sampling error but also because the bias is relatively larger when the true value is small.

These results point to yet another complication to the already difficult problem of statistically evaluating the relationship between police--either police officers or police expenditures per capita--and crime levels. For a discussion of these other problems see [4], [11], [21].

Before concluding, the limitations of the data upon which this study is based should be noted. First, we have used city data; much of the statistical analyses of crime rates have utilized state level data. It is uncertain whether the findings of this analysis would extend to the more aggregative level data. Further, the size range of the cities is relatively restricted; most of the cities are quite large. Finally, the victimization survey data upon which we have relied for crime reporting data also have measurement problems [13].

Conclusions:

We have shown that there exists a systematic component to the variation in crime underreporting at the city level. The implications of this component are more general than those which follow from the random component. That is, the systematic dependence of the crime reporting ratio on the level of reported crime will bias all of the coefficients in the crime equation, not just the sanction variables formed with the reported crime rate in the denominator. This bias will operate to produce a spurious effect of each variable on the crime rate, independent of any true effect. In this sense, it operates like the random variation in crime underreporting on sanction variables, but with opposite effects.

It is interesting to note that the size of the general bias produced by the dependence of reporting on the crime rate, in the simultaneous equation model, depends upon the size of the punishment coefficient, $\alpha_2$, a variable which has been shown to be biased by the random variation in reporting. It is beyond the scope of this paper to explore the combined effects of these two biases. However, since the effects of the random variation have been analyzed only in very simple models, it appears that monte carlo studies will be required to analyze both sources of bias in simultaneous equation models.

The importance of measurement error effects stressed by the report of the Panel on Research on Deterrent and Incapacitative Effects appears to be justified. However, <u>a priori</u> we cannot be sure as to the <u>direction</u> of these effects. Consequently, if statistical studies based upon reported crime rates are to provide any policy guidance it is important that the total impact of all of the sources of bias be established.

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